CAPP 30254: Assignment 2 Write-up

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April 12, 2016

1 Goal

In this exercise, we attempt to predict the likelihood of serious loan delinquency given a series borrower characteristics. The goal of this exercise was to import, describe, visualize, and clean a dataset of borrower data with loan delinquency status on which we could build a predictive model, then predict values for a set of borrowers for which the actual loan delinquency was unknown.

2 Statistics

First, we have a table of summary statistics for the training dataset. Standard deviation is indicated by "std". The median is indicated by "50%".

	Unnamed: 0	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age
count	150000	150000	150000	150000
mean	75000.5	0.06684	6.04844	52.2952
std	43301.4	0.249746	249.755	14.7719
min	1	0	0	0
25%	37500.8	0	0.0298674	41
50%	75000.5	0	0.154181	52
75%	112500	0	0.559046	63
max	150000	1	50708	109
missing values	0	0	0	0

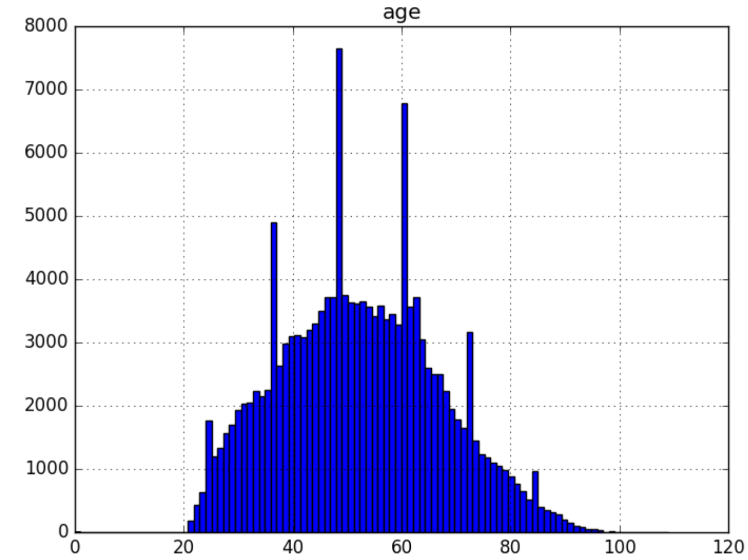
	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome
count	150000	150000	120269
mean	0.421033	353.005	6670.22
std	4.19278	2037.82	14384.7
min	0	0	0
25%	0	0.175074	3400
50%	0	0.366508	5400
75%	0	0.868254	8249
max	98	329664	3.00875e+06
missing values	0	0	29731

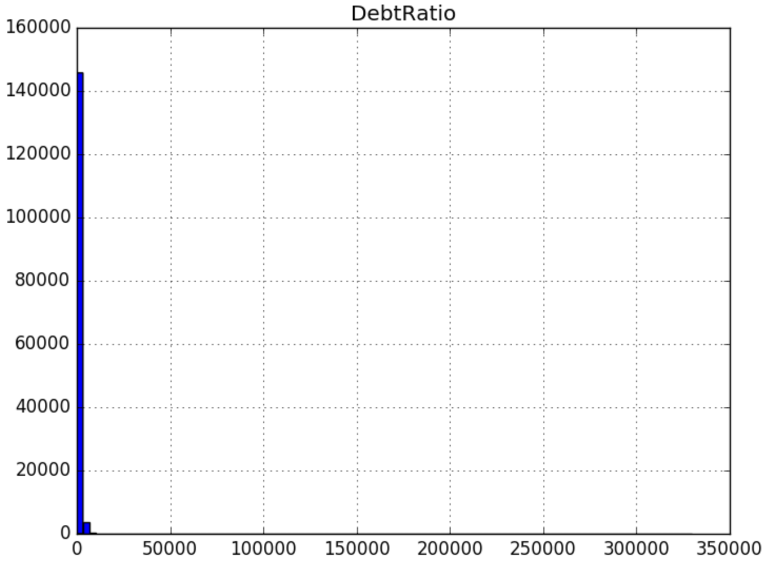
	NumOfOpenCreditLinesAndLoans	NumOfTimes90DaysLate	NumRealEstLoansOrLines
count	150000	150000	150000
mean	8.45276	0.265973	1.01824
std	5.14595	4.1693	1.12977
min	0	0	0
25%	5	0	0
50%	8	0	1
75%	11	0	2
max	58	98	54
missing values	0	0	0

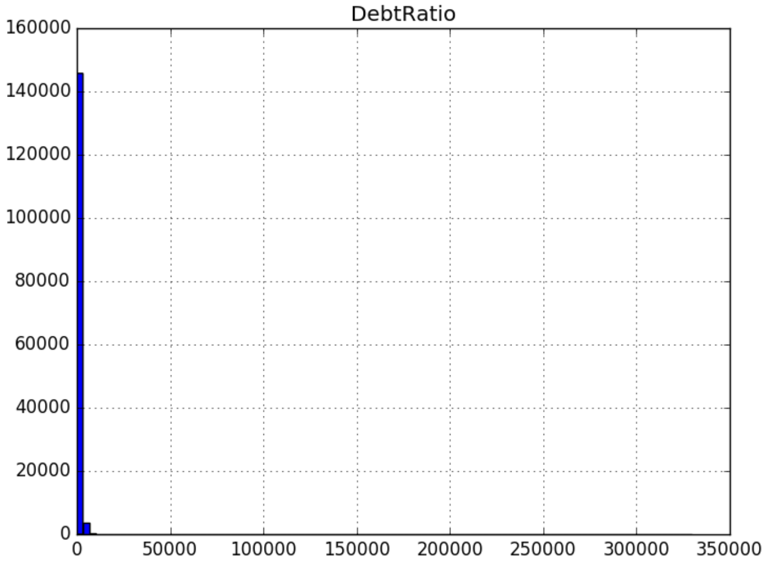
	NumberOfTime60-89DaysPastDueNotWorse	NumberOfDependents
count	150000	146076
mean	0.240387	0.757222
std	4.15518	1.11509
min	0	0
25%	0	0
50%	0	0
75%	0	1
max	98	20
missing values	0	3924

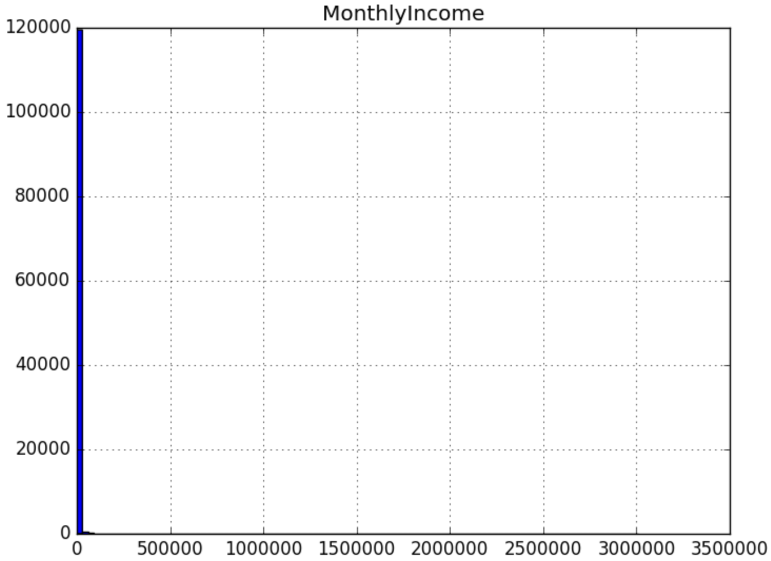
3 Histograms

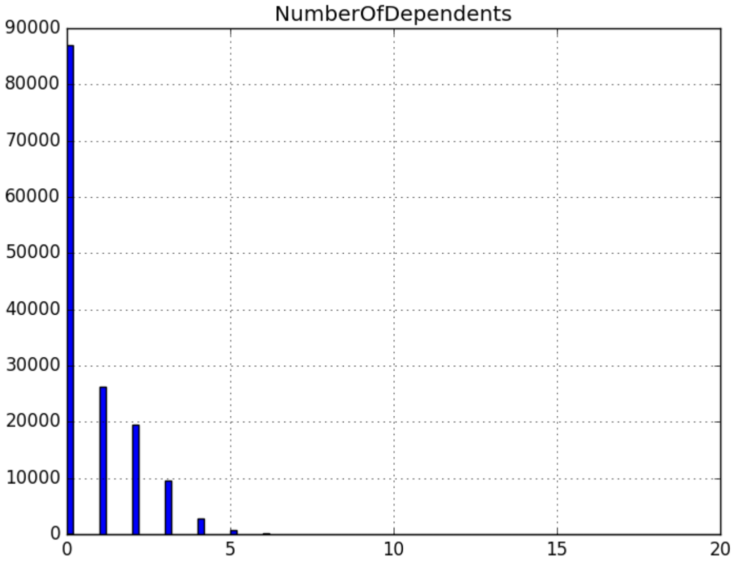
Below are a series of histograms indicating the distributions of numeric variables in the training dataset.

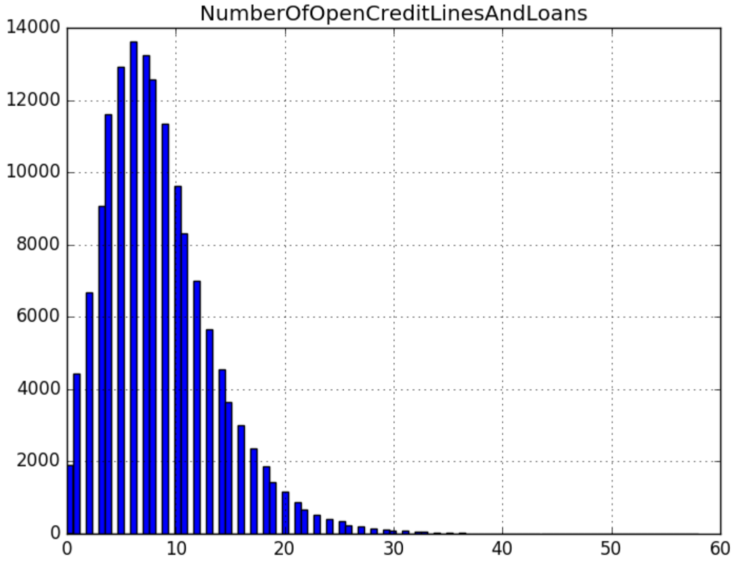


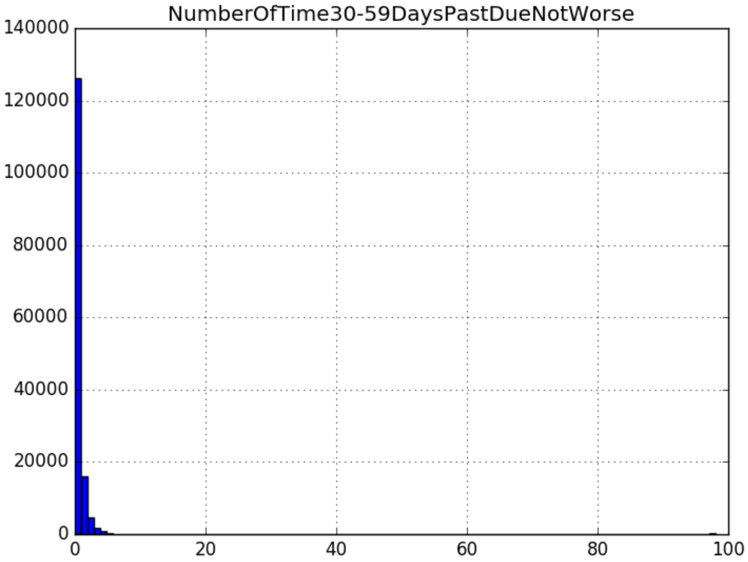


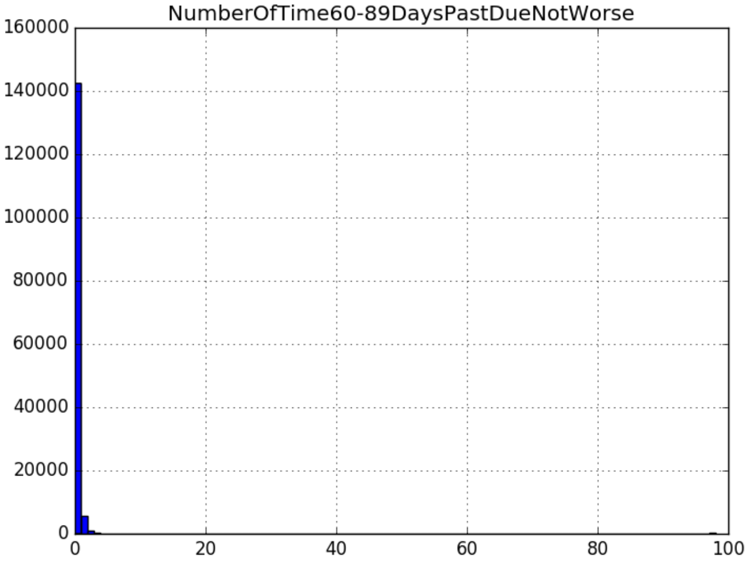

DebtRatio
160000
140000
120000
100000
80000
60000
40000
20000
0
0
50000
100000
150000
200000
250000
300000
350000

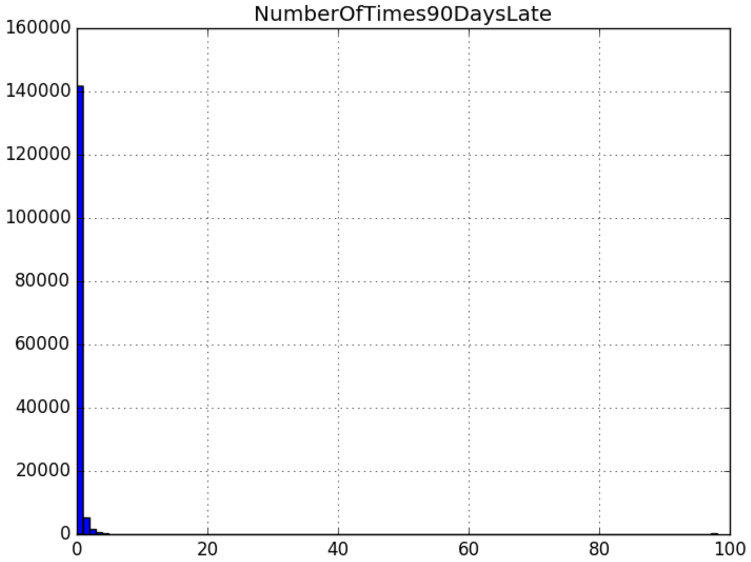

MonthlyIncome
120000
100000
80000
60000
40000
20000
0
0
500000
1000000
1500000
2000000
2500000
3000000
3500000

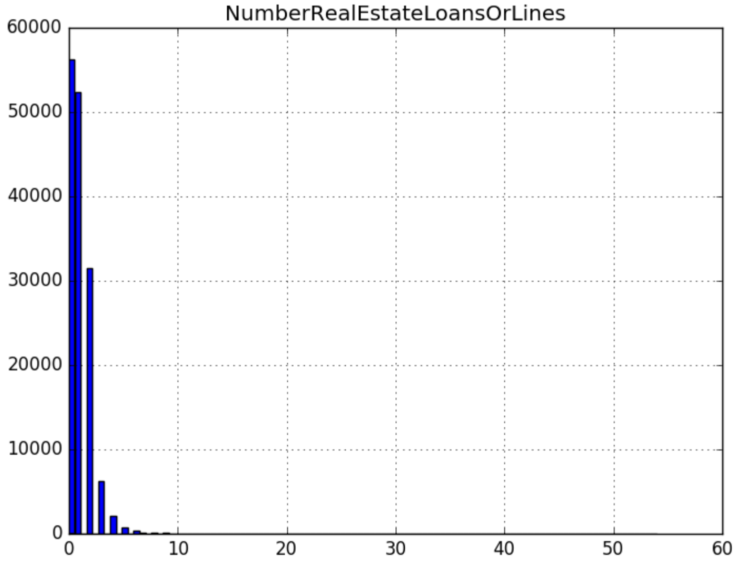

NumberOfDependents
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
0
5
10
15
20

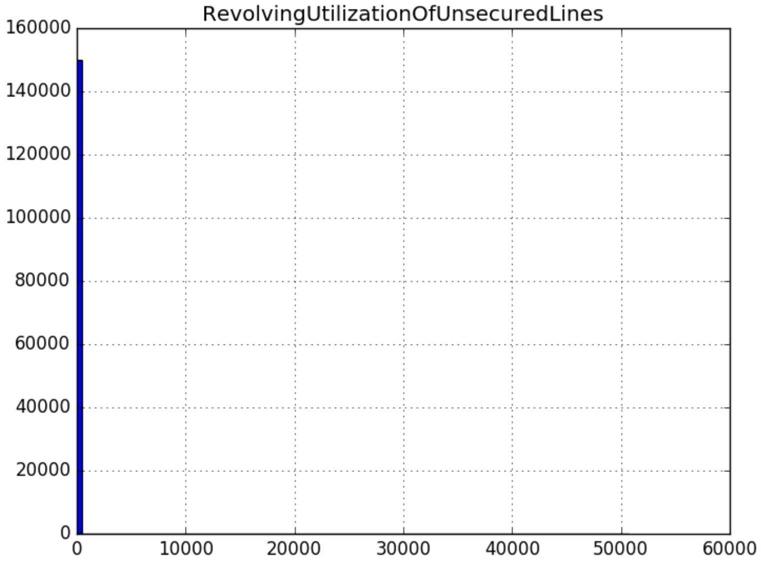

NumberOfOpenCreditLinesAndLoans
14000
12000
10000
8000
6000
4000
2000
0
0
10
20
30
40
50
60

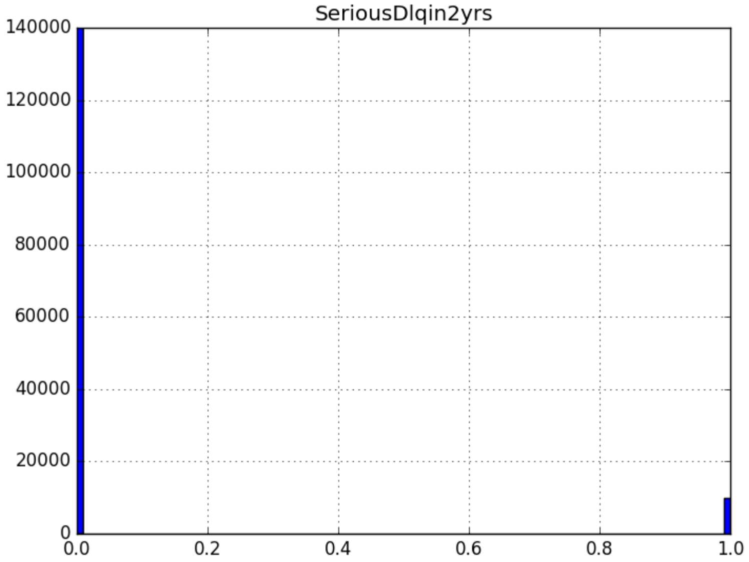

NumberOfTime30-59DaysPastDueNotWorse
140000
120000
100000
80000
60000
40000
20000
0
0
20
40
60
80
100


NumberOfTime60-89DaysPastDueNotWorse
160000
140000
120000
100000
80000
60000
40000
20000
0
0
20
40
60
80
100


NumberOfTimes90DaysLate
160000
140000
120000
100000
80000
60000
40000
20000
0
0
20
40
60
80
100


NumberRealEstateLoansOrLines
60000
50000
40000
30000
20000
10000
0
0
10
20
30
40
50
60


RevolvingUtilizationOfUnsecuredLines
160000
140000
120000
100000
80000
60000
40000
20000
0
0
10000
20000
30000
40000
50000
60000


SeriousDlqin2yrs
140000
120000
100000
80000
60000
40000
20000
0
0.0
0.2
0.4
0.6
0.8
1.0

As we can see, a number of the distributions demonstrate extremely long right tails: most of the data is concentrated at low values, but some are at very high values.

Our variable of interest, in the last histogram entitled ”SeriousDlqin2Yrs”, shows that in the training dataset most of the individuals demonstrated no serious delinquency, but that a small subset showed very high delinquency rates.

4 Data Imputation

All of the variables in the dataset are numeric. In order to impute missing values, I simply filled the values the missing values with the mean for that variable. This did not seem like an unreasonable choice given the size of the dataset and the continuous rather than the discrete nature of the variables (in which case mean values more sensitive to categorical regularities might have been used).

This dataset with filled values is included in the repository ”predicted

5 Model Choice and Predicted Values

In order to predict the values I tried three different machine learning methods [1]. The best method, called the K-Nearest Neighbors Method (which tries to decide on an unknown type by looking at those what who are most similar on a range of characteristics), which resulted in an accuracy of .934. Unfortunately, this accuracy is not very different from simply assuming all of the borrowers are *NOT* delinquent. In our predicted values (found in the folder ”data_output/predicted_values.txt”) for the test dataset, only one or two borrowers were predicted to be delinquent. In the future, I hope to improve upon this accuracy metric by trying a wider variety of models and model specifics.

The choice of a nearest neighbours method rather than a more probabilities focused logistic regression method seems reasonable because the dataset demonstrates that in probability all individuals will not be delinquent, but broad similarity between individuals across all characteristics may predict risk well.

[1] The three classifiers attempted were K-Nearest Neighbours, Logistic Regression, and Linear SVC